The research was supported by National Science Foundation Grant.

\[ \begin{align*}
\left\{ \xi \right\} & \leq \begin{bmatrix}
0 & 0 \\
-1 & r
\end{bmatrix} \\
\left\{ \eta \right\} & \leq \begin{bmatrix}
0 & 0 \\
-1 & r
\end{bmatrix}
\end{align*} \]

In terms of the second and fourth order spectra of the series in terms of the second and fourth order spectra of the series, for example, the fourth order spectrum has been shown to be approximately normal and large sample expression have been given for its variance, Bartlett (1969), and Andrews (1970, 1974), Brillianger (1979).

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\[ \frac{\hat{\alpha} - \alpha}{\sigma} \sim t \]

The present paper introduces a direct procedure for drawing estimates of the spectrum that appear.

A result that is often made use of in practice, in this

\[ \sum_{i=1}^{n} \left( x_i - \bar{x} \right)^2 \]

(5.1) \[ (r) \]

(6) \[ (r) \]

(7) \[ (r) \]

(8) \[ (r) \]

(9) \[ (r) \]

where \( z \) and \( x_i \) are independent variables.

The variance estimates from the inversion into (1.3) or (1.4) are available for use in deriving confidence intervals on such means.
distribution of the variate

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) \]

with \( \mu \) fixed. The asymptotic

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) \]

is asymptotically distributed as

\( t \) independent of \( \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) \)

as \( n \to \infty \).

It follows from Theorems 4.4 and 4.5 of Brillinger (1975).

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) = \chi(\frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu)) \]

where

\[ \chi = \begin{cases} \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) \\ \mu \end{cases} \]

is the estimate of \( \mu \).

Second order spectra

Another parameter that will be required is the

a stationary series.

The problem of constructing a confidence interval for the mean of

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) = \chi(\frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu)) \]

when \( \epsilon_i = 0 \) is the problem of constructing a confidence

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) = \chi(\frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu)) \]

available.

Therefore the estimate of \( \chi(\frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu)) \)

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) \]

is an estimate of \( \chi(\frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu)) \)

as \( n \to \infty \).

Appropriate confidence intervals for \( \epsilon \) may

\[ \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (X_i - \mu) \]

be used.
(11.2) \[ \hat{\theta}_n = \frac{1}{n} \sum_{i=1}^{n} X_i \]

The quantity \( \hat{\theta}_n \) is asymptotically normal with mean \( \theta \) and variance

\[ \text{Var}(\hat{\theta}_n) = \sigma^2 / n \]

The mean of a normal sample is asymptotically normal with mean \( \theta \) and variance \( \sigma^2 / n \).

It follows from the central limit theorem that

\[ \frac{\hat{\theta}_n - \theta}{\sigma / \sqrt{n}} \overset{d}{\rightarrow} N(0,1) \]

and expression (2.6) is essentially the usual t-probabilistic confidence interval for the mean of a normal sample.

If one takes \( \nu = \frac{1}{2} \) in (2.7), then

\[ \chi^2(\nu/2) \]

is a random variable with \( \nu/2 \) degrees of freedom. For a given value of \( \nu \), large \( \nu \) results in

\[ \lambda = \left( \frac{\nu}{2} \right) \chi^2(\nu/2) \]

where for student's t on \( \nu \) degrees of freedom.
where \( \xi^2 \) is given by (2.3) and (2.4).

\[
\xi_T = \sqrt{\frac{2}{g+1}} \left[ \frac{X}{g} \right] + n \xi^2 \frac{1}{g+1} \left[ \frac{X}{g} \right] - n \xi^2 \frac{1}{g+1} \left[ \frac{X}{g} \right]
\]


In summary, an approximate 100(1-\( \alpha \))% confidence interval

\[
\left( X - t \sqrt{\frac{X}{g} + n \xi^2 \frac{1}{g+1} \left[ \frac{X}{g} \right]} \right) < X < \left( X + t \sqrt{\frac{X}{g} + n \xi^2 \frac{1}{g+1} \left[ \frac{X}{g} \right]} \right)
\]

for the parameter \( \xi^2 \) is provided by

1. This change will have no asymptotic effect.
2. Under the asymptotic estimate, the estimate of \( \xi^2 \) based on its variance, under assumption (2.3),

\[
\left( \frac{X}{g} \right) - (1) \frac{X}{g} \left[ \frac{X}{g} \right] = (1) \frac{X}{g}
\]

will be defined by

\[
\xi^2 \text{ will be defined by the series in the case of interest where } \xi^2 \neq 0.
\]

\( \xi^2 \) is the series of interest where \( \xi^2 \neq 0 \).

It is interesting to note that the term within \( \left[ \frac{X}{g} \right] \) freedom.

The distribution of \( X^2 \) by students, with 2k degrees of freedom, is approximately the chi-squared distribution with \( 2k \) degrees of freedom.

It is also worth remarking that the test statistic for the term \( \xi^2 \) is \( (1) \frac{X}{g} \left[ \frac{X}{g} \right] \) for the series \( (1) \frac{X}{g} \).

The test statistic for the term within \( \left[ \frac{X}{g} \right] \) is defined as

\[
\left( \frac{X}{g} \right) - (1) \frac{X}{g} \left[ \frac{X}{g} \right] = (1) \frac{X}{g}
\]

and \( \xi^2 \) is defined as

\[
\xi^2 = \frac{(g+1)}{2} \left[ \frac{X}{g} \right] - \frac{2g}{g+1} \left[ \frac{X}{g} \right]
\]

In practice, this estimate may be formed by first evaluating the estimate \( \frac{X}{g} \) of the matrix \( (1) \frac{X}{g} \) and then using the estimate \( \xi^2 \) to.

The chi-squared test \( (2.3) \) requires the use of the test statistic \( (2.3) \) and its distribution with 2k degrees of freedom. A. M. BEYNDT
of (2.11),

the set of (2.27) and then to evaluate the quadratic form

\[
(5.9) \left\{ \left( \sum_{i=1}^{n} z_i^2 \right) / (n) \right\} \left( x - \bar{x} \right) + \left( \sum_{i=1}^{n} z_i \right) \left( x - \bar{x} \right)
\]

will prove simpler to estimate the power and cross spectra.

In terms of the set of (2.4), \( \mu \) is given by (2.9).

\[
(9.4) \begin{pmatrix} \beta(x) \\ \beta(y) \end{pmatrix} = \begin{pmatrix} \alpha \end{pmatrix} + \begin{pmatrix} \omega \end{pmatrix}
\]

where \( \beta(x) \) is given by (2.9).

Based on the

\[
\left( \sum_{i=1}^{n} z_i \right) \left( x - \bar{x} \right) + \left( \sum_{i=1}^{n} z_i^2 \right) \left( x - \bar{x} \right)
\]

integrated, is provided by

at the end of Section 2.2 and approximate 100% confidence

in the manner of expression (2.9). Following the discussion

\[
(5.4) \begin{pmatrix} 0 \end{pmatrix} \begin{pmatrix} \sum_{i=1}^{n} z_i \end{pmatrix}
\]

in greater use is to perform the sample crosscorrelation function

\[
(1.4) \begin{pmatrix} 0 \end{pmatrix} \begin{pmatrix} \sum_{i=1}^{n} z_i \end{pmatrix}
\]

to the terms \( \begin{pmatrix} 0 \end{pmatrix} \begin{pmatrix} \sum_{i=1}^{n} z_i \end{pmatrix} \)

in the manner of expression (2.9) and the discussion

\[
(1.1) \begin{pmatrix} (0) \sum_{i=1}^{n} z_i \end{pmatrix}
\]

in greater use is to perform the sample crosscorrelation function.


A further means of examining a part of stationarity

\[ \text{is the coefficient function} \]

\[ \text{of the estimate of \( z \) in expression (1.7).} \]

Cf. expression (1.3).

[\( \alpha \), \( \beta \) and \( \gamma \)]

\[ \text{are approximations to} \]

\[ \text{the co-variance matrix \( \Sigma \).} \]

\[ \text{In the case of} \ x \ y \ z \ \text{and} \ (n) \ \text{we}

\[ \text{have to take into account the effect of}\]

\[ \text{the dependence on} \ x \ y \ z \ \text{and} \ (n) \ \text{which}

\[ \text{is independent of} \ x \ y \ z \ \text{and} \ (n) \ \text{are approximated by} \]

\[ \text{an estimate of the form} \]

\[ \text{where} \end{quote}
REFERENCES

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Abstract

Approximate confidence intervals are constructed for the auto and cross-covariance functions and for the auto and cross-correlation functions via the stationarity and the auto and cross-covariance function respectively of a discrete stationary time series.

Contents

Mathematical Statistics

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Volume A

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